TITLE: Processing and Fusion of Electro-Optic Information

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Introduction

The UK Defence Evaluation and Research Agency (DERA) has been researching over many years the use of knowledge-based techniques for the automation of information fusion within combat management systems functions. All-source automated data fusion techniques have successfully been demonstrated at the platform level and are currently embodied in a testbed called CMISE (Combat Management Integrated Support Environment). This makes use of own platform sensor data and tracks from other platforms via datalink for the automatic construction of the platform's tactical picture.

The Data Fusion Module (DFM) within CMISE correlates at two levels, track and multi-track. Track correlation joins tracks from similar sources to form multi-tracks and multi-track correlation joins multi-tracks (from dissimilar sources) to form vehicles. Tracks and multi-tracks are correlated by a rule-based system using multi-hypothesis techniques supported by probability based algorithms.

The data sources currently correlated by CMISE are radar, Electronic Support Measures (ESM), datalink, sonar, Identification Friend or Foe (IFF), plans and geographic information. This paper describes the modelling of an EO sensor and the effects of including data from such sensors in a fused tactical picture.

DERA has been evolving the capabilities of CMISE in support of the applied research programme for over ten years. The requirement for a substantial increase in the level of automated support system comes from:

- a rapid increase in the amount of data available to Command. More sensors are available, producing more data;
- in the drive to improve the extent and quality of tactical information, automated methods are potentially faster, more reliable and more consistent than manual methods;
- increases in hostile target mobility and weapon lethality particularly in the littoral battlespace, stressing the importance of accurate and timely identification of targets;
- pressures to reduce platform through-life costs, particularly through reduction of manning.

As well as addressing the above issues, automating the tactical picture compilation process allows operators to focus attention on situation assessment and resource allocation (actually fighting the ship) instead of being consumed by the mundane and repetitive track fusion and identification tasks for which automation is more suited.

Data Fusion concept

Data fusion in this context is the process of combining multiple elements of data from disparate sources in order to produce information of tactical value to the Command, hence reducing the information load on operators and improving the tactical picture quality. This data, both real-time and non real-time, includes ESM, radar, IFF, infrared, sonar, intelligence information, Operating Procedures and Own Force Plans. Sources may be similar, such as radars, or dissimilar such as electronic emissions and infrared.

Data fusion usually occurs either at the plot (measurement) level or at the track level. At the plot level data is fused using the raw sensor output. At the track level data is fused after a track extraction and state estimation process. Different sensor types produce different types of data, for example position and velocity for radar, bearing and emitter parameters for ESM and bearing and acoustic signature for passive sonar. Fusion between plots or tracks is only possible if two sets of data contain measurement of at least one similar attribute, e.g. fusion of radar tracks with ESM tracks by bearing analysis.

In DFM new tracks always form a new multi-track and (tentative) vehicle (V'). The track is then compared against other vehicles' tracks and multi-tracks in an

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attempt to correlate it. If the correlation is possible a tentative link is established between the new track and the associated multi-track. New track updates either confirm correlation or the correlation fails. A track can have tentative links with more than one multi-track. A correlation link will confirm when only one tentative link remains. If there are no tentative correlations the track is classified as an established vehicle (V). Figure 1 shows this process.

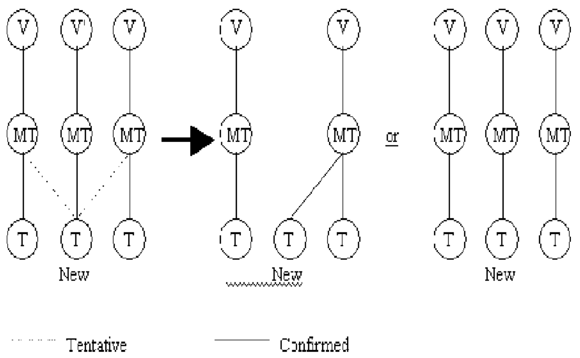

Figure 1. Track correlation.

Other, more complex, processes have also been developed to implement multi-track correlation, repair, track confirmation and the inclusion of collateral data, such as plans, geographic, etc.

Following track and multitrack correlation, a function then combines identity evidence associated with each contact to establish its platform identity and hostility. Many categories of stored information are used to identify contacts, such as structural models to define the relationship between measured contact attributes (acoustic/radar signatures, radio frequency emissions, etc) and contact classes, and behavioural models to relate the temporal behaviour (velocity, altitude, etc) and spatial behaviour (contact formations, weapons ranges) to contacts and events.

The production of the fused tactical picture makes available the following types of information:

- position and velocity,
- identification of contacts and associated uncertainty or ambiguity between multiple possible contacts,
- situations of military importance resulting from individual contact locations, behaviour or aggregate behaviour of multiple contacts,

CMISE modes of operation

The CMISE test bed can produce the real-time tactical picture using data from either live real world sensors (and collateral sources) or recorded real world sensor data or simulated sensor data. CMISE receives tracks from all sensors when in live mode. A simulator/stimulator system called the Object Oriented Programming scenario data generator (OOPSDG) is used when simulated data is required. This system stores and maintains the position and identification of contacts in a scenario together with relevant environmental data. The system uses sensor models (plus contact and environment information) to produce tracks that are output to CMISE. OOPSDG also contains clutter models for each sensor type to produce random clutter tracks (clutter is already present if recorded sensor data is used).

OOPSDG currently contains sensor models for radar, sonar, ESM and IFF. This paper will now describe recent work towards developing an additional electro-optic (EO) sensor model within OOPSDG. It describes performance estimates found prior to producing the completed model.

EO sensor model requirements

The drivers for production of an EO sensor model for inclusion in OOPSDG in order to stimulate CMISE are:

- to investigate the benefits of inclusion of EO sensor data in the fused tactical picture,
- to determine the tactical picture requirements of an EO sensor specification.

Previous work under the current project, investigated the potential use of EO sensors in a naval context. This study concluded that a great deal of tactically significant information is available from EO sensor systems, especially during low intensity operations. An EO sensor model for stimulation of CMISE was proposed as a means to investigate the possible benefits through improved tactical picture quality. All types of EO sensor were investigated for potential to improve their contributions. However, the initial EO sensor model was based on that most likely to be fitted to near future Royal Navy (RN) warships ensuring that the modelled sensor capability matched that of future RN platforms.

The model will be used to determine the effects on automated tactical picture compilation of such attributes as update rate, field of regard, false alarm rate, bearing and elevation accuracy, and detection, recognition and classification range requirement limits, (i.e. the minimum values necessary for improved tactical picture quality).

EO model description

The initial EO model will be based on an infra-red search and track (IRST) sensor, which is primarily designed for detection of sea-skimming missiles. For this reason, the IRST field of view is concentrated on a region a few degrees either side of the horizon and image processing to detect point source targets (point source targets are objects that are at sufficient range to fill only one pixel on the IRST detector array).

An initial equation was provided by the EO sensors group within DERA to calculate the infrared signal strength from a generic sea-skimming missile as a function of atmospheric path attenuation, target IR signature, range and processing threshold, Equation 1.

$$Signal = \frac{\left(T_h + T_s(\sin\theta)^P\right)\exp(-\sigma R)}{S\,R^2} - Th$$

Equation 1. IR signal strength.

Where T_h and T_s are the target IR signals at zero range for head-on and side-on views respectively, P is a signature modification factor, R is the range between target and sensor, σ is the atmospheric absorption, θ is the viewing aspect of the target measured from head-on, Th is the processing threshold of the sensor and S is the sensor noise equivalent irradiance.

The equation used to determine target signal strength is accurate to a first approximation. The equation does not account for secondary factors affecting IR signal strength such as scintillation or solar heating of target surfaces. These factors produce changes in IR signal strength smaller than the errors in Equation 1 and were therefore neglected. Using Equation 1 to calculate object detection range gave a maximum error (in range) of 15%. A low fidelity model was developed as it best typified EO sensor detection behaviour at a level good enough for tactical picture fusion.

Detection of a real world object is not deterministic and has a random component. Objects at a given distance from a sensor have a certain probability of not being detected even if the signal strength given by Equation 1 is greater than the detection threshold (and also a non-zero probability of being detected when the signal strength is below the detection threshold). The statistical nature of object detection is modelled by the cumulative normal distribution, Equation 2. Standard statistical tables of the normal distribution give critical values of signal strength for given detection probabilities.

$$Pd = \int_{-\infty}^{signal} \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{x^2}{2}\right)} dx$$

Equation 2. Probability of object detection.

We desire the interval of range values over which the probability varies significantly. Equation 1 cannot be solved explicitly to find the range for a given signal and threshold. An iterative formula was therefore used to solve the equation and determine the minimum and maximum range for likely first detection of an object (i.e. the 99% and 1% detection probability ranges respectively), Equation 3.

$$R_{i+1} = R_i - \frac{R_i^2 A - e^{-\sigma R_i}}{2AR_i + \sigma e^{-\sigma R_i}}$$

Equation 3. Detection range iteration formula

Where $A = S(Signal + Th)/(T_h + T_s(\sin\theta)^P)$ and R_i tends towards the correct range as i increases.

Iterative calculations are computationally time consuming and Equation 3 was therefore not implemented as the sensor equation in the OOPSDG EO model. Target IR signature data was obtained and used with Equation 3 to produce tables of detection range (for both 99% and 1% detection probabilities) as a function of target viewing aspect, atmospheric absorption, target IR signal and processing threshold. An estimated equation for a curve of best fit for Equation 3 (not using iteration) was obtained. A least squares approximation was performed for each target type at threshold intervals of one (from three to ten). The least squares approximation produced the coefficients for the detection range equation of best fit, Equation 4.

$$DetectionRange = C_1\alpha^4 - C_2\alpha^3 + C_3\alpha^2 - C_4\alpha + C_5 - C_6\theta^2 + C_7\theta$$

Equation 4. Generic detection range equation.

Where C_i is constant i, α is the atmospheric absorption and θ is the target viewing aspect measured from head-on. Equation 4 will be implemented in OOPSDG to model generic detection of targets. A linear relationship between detection probability and range will be assumed between the calculated values for 99% and 1% detection probability ranges. It was found that Equation 4 was a best fit for modelling detection probabilities of fixed wing aircraft and missile target types. Equation 5 was found to best model detection probabilities for ship and helicopter target types.

$$DetectionRange = C_1\alpha^{-C_2} - C_3\alpha^2 + C_4\theta - C_5$$

Equation 5. Generic detection range equation for ships and helicopters.

Limitations of EO model

The initial EO model described has the following limiting factors:

- The model applies to point source targets only; a point source target is detected when the target signal strength at the detector is greater than the detector threshold, i.e. point source target detection is based only on IR signal strength. Objects that fill more than one pixel in the detector array (extended objects) may be detected using techniques other than IR signal strength measurement, for example object detection based on target shape. Object detection models using methods other than IR signal strength will require different equations.

- Equation 1 applies only for target viewing aspect from head-on to side-on (0-90°); the initial range detection equation was derived for a generic sea-skimming missile. For such target types it is a reasonable assumption that the target will most likely be viewed head-on or near to head-on (i.e. target travelling towards the sensor on Ownship). Equation 1 has been modified to account for rear-on IR signals for all target types.

- Secondary factors affecting target IR signal strength have been neglected; it is planned to enhance the fidelity of the EO sensor model by accounting for secondary factors as the next iteration of the model.

- IR clutter has not been modelled; IR clutter, from cloud edges, sea glint, birds etc, are a major limiting factor for automating target detection using a real EO sensor. An IR clutter model is necessary for the completeness of the sensor model. Such a model is to be included in the next phase of the project.

EO sensor model proof of concept

The equations described previously have been used to produce a PC version of the EO sensor model. The PC version was coded in order to verify the sensor model concept. This version of the EO sensor model used a look-up table containing constants for four different target types as inputs to Equation 4. Equation 4 was used to determine the 99% and 1% detection probability ranges for a target. One percent of detectable targets were randomly undetected and one percent of undetectable targets were randomly detected to reflect the statistical nature of the target detection process. A linear relationship between detection probability and range was assumed for ranges between the calculated 99% and 1% detection probability ranges.

Validation of the PC EO model (and therefore the supporting model equations) was achieved by comparison of model calculated detection ranges and real target trials recorded detection ranges. The atmospheric absorption coefficient was not available for trials recorded data. It was approximated by a value of 0.1 representing good IR transmission through the atmosphere (or 'good' weather conditions, i.e. a low amount of water vapour content in the atmosphere) through to a value of 0.9 for poor IR atmospheric transmission. Differences between calculated and measured detection ranges were within the errors of the calculated and measured values for target data available.

Data fusion model investigation of EO contribution to tactical picture

A faster than real time data fusion model separate from CMISE, has been developed in order to rapidly assess data fusion performance prior to use of CMISE. The data fusion model uses simplified sensor models for radar, ESM, sonar and IR sensors to produce a tactical picture [1]. Targets are given statistically random positions and motions. The simplified sensor model equations are then used to determine target detections. Tracks are fused in a similar manner as the data fusion process of CMISE described previously. The data fusion model outputs measures of tactical picture quality, such as picture completeness, picture correctness, correct correlations, etc.

The data fusion model has been used to perform a preliminary investigation of the effects of including EO sensor data in a fused tactical picture. Two sets of data were obtained. One set of data corresponded to all sensor data including EO. The second set omitted the EO sensor. Averages for each tactical picture quality metric were calculated for ten, twenty minute 'scenarios', both with and without EO sensor input.

Results show that tactical picture quality was improved with the inclusion of EO sensor data.

Inclusion of EO sensor data improved tactical picture correctness[1] owing to the accurate angular measurement of EO sensors (compared to that of other sensors): the accurate bearing (and elevation) data from EO sensors restricts the volume (and thus number of possible incorrect associations) considered in the fusion process resulting in a more correct tactical picture. This fact was verified by observing a directly proportional relationship between EO sensor bearing accuracy and the number of correct associations (and hence, tactical picture correctness).

The inclusion of EO sensor data reduced tactical picture completeness[2]; the inclusion of additional sensor data in the tactical picture results in increased numbers of associations that have to be made for a complete tactical picture. The reduced tactical picture completeness shows

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[1] Tactical picture correctness is given as the number of correct pairwise associations made by the fusion system divided by the total number of pairwise associations made.

[2] Tactical picture completeness is the mean number of correct objects, where an object is considered correct if: all the objects tracks come from the same real world object; all the real world object associated tracks are associated with the picture object; and at least one track supporting the picture object has a current sensor report.

that a smaller proportion of the increased number of associations were achieved when EO sensor data was included in the tactical picture compilation process.

Inclusion of EO sensor data increased the number of incorrect and missed correlations. Inclusion of EO sensor data increases the number of possible correlations between tracks. The resulting percentage of incorrect and missed correlations was lower (improved) when EO sensor data was included in the tactical picture fusion process. The relationship between inclusion of EO sensor data and the percentage of incorrect and missed correlations was verified by increasing EO sensor bearing accuracy and observing increased incorrect and missed correlation percentages (as well as increased total number of possible correlations).

Future Work

EO sensor model enhancement

The EO sensor model described in this paper is to be further developed in the following aspects:

- Further investigation of EO sensor data fusion contribution; it is proposed that the fusion of EO sensor data with other sensor sources be investigated in pairs of sensors, e.g. radar and EO or ESM and EO,

- Full investigation of EO sensor data fusion; it is proposed that the contribution of EO sensor data to the tactical picture be investigated using CMISE and the sensor models in OOPSDG,

- Extension of EO sensor model; imaging sensors, such as EO, offer improved situation awareness to Command as a result of Command being able to actually see targets (captured in an image). The potential benefits to Command includes accurate target classification and identification, target behaviour and intentions assessment and battle damage assessment. Measurements of this type are most accurate for extended targets in an image. It is proposed to enhance the current EO sensor model to include sensor functionality for extended targets.

- Modelling of different EO sensors; the current model simulates the output of an IRST sensor. Other EO sensors have a wider field of regard, detect target signals in different wavelengths and measure target range offering Command greater situational awareness [1]. The EO sensor model is to be extended to incorporate features of other EO sensors to investigate the potential contributions to the tactical picture and situational awareness.

- Extension of target database; the current target database is limited by the availability of measured target signal data. The current target database contains IR signature data for thirty target types. The target signal database will be extended in the availability of measured target EO signal data.

Summary

The automated production of the tactical picture in the CMISE test bed using sensors and collateral data has been outlined. The current lack of EO sensor data in the system has been identified and is being addressed by the work described.

The development of an EO sensor model as a track input to CMISE is reported. The current EO sensor model is based on the possible IRST system fit on future RN platforms. Limitations of the model have been discussed and future work to enhance the model has been described.

References

1. Miles, J.A.H. & Metcalfe, G. 'Picture Quality Control and Measurement' presented at 'Defence System and Equipments International' DSEi 99, Chertsey UK, September 1999.

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